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Human stopping strategies in multiple-target search

Seung-Kweon Hong*

Department of Industrial and Management Engineering, Chungju University, 123 Geomdam-ri Iru-myeon, Chungju, Chungbuk 380-702, South Korea

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Abstract

All visual search tasks must stop at some point. A reasonable decision for stopping times during search tasks is critical to search task performance. This paper presented an economic model for determining an optimal stopping time. The optimal stopping time model of a one-target search was extended to that of a multiple-target search. Additionally, three optimal stopping time usage strategies: a self-stopping strategy, an externally forced stopping strategy and a hybrid-stopping strategy, were compared under several task conditions. The self-stopping strategy resulted in a better performance than either of the other two under most task conditions. The higher the degree of time pressure, and the more ambiguous the pre-information on the number of targets in a search field, the lower the relative effectiveness of the self-stopping strategy. However, even under the worst task conditions (i.e. high time pressure condition), the performance of the self-stopping strategy was not lower than the other stopping strategies. Such effectiveness of the self-stopping strategy might be caused by the human observers' ability to use an extended set of decision cues to heighten awareness of the situation.

Relevance to industry

The results of this work can be used to plan visual inspection tasks for manufacturing and aviation maintenance and to train inspectors.

Keywords: Stopping strategy; Stopping time; Economic model; Multiple targets; Visual search

1. Introduction

When should a visual search task be terminated? How do human observers decide the stopping time? These questions are important in research issues related to visual search performance. However, in spite of their importance in visual search

*Corresponding author. Tel.: +82-43-841-5304; fax: +82-43-841-5300.
E-mail address: skhong@chungju.ac.kr (S.-K. Hong).

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tasks, such topics have not been extensively studied.

Chun and Wolfe (1996) were interested in the decision mechanism for determining a stopping time. They proposed a model for termination of visual searches in the context of the Guided Search 2.0 model (Cave and Wolfe, 1990; Wolfe, 1994; Wolfe et al., 1989). This model was named the "activation threshold model." According to this model, pre-attentive processes are used to evaluate the probability of each item in the search field being the target. In the following serial processes, the items are examined in decreasing order of probability that they are the target. The searches are terminated when no remaining items have probabilities above a termination threshold.

In contrast to proposing and investigating a human decision mechanism for search termination, under an assumption that human observers use the best search termination mechanism in the view of economics, optimal stopping time models have been presented (Tsao et al., 1979; Morawski et al., 1992; Karwan et al., 1995; Drury and Chi, 1995; Baveja et al., 1996). However, those models were limited to the visual search task for finding one target. In this study, the optimal stopping time model of the one-target search is extended to that of a multiple-target search. Additionally, a laboratory experiment is performed in order to investigate which optimal stopping time usage strategy is most effective.

2. Optimal stopping time models

2.1. Related studies

An optimal stopping time model was initially proposed by Tsao et al. (1979). The optimal stopping time was the time at which the expected value of a search task is maximized. The expected value of a search task was represented as a function of search time, considering a search performance model, benefits of detecting a target (V), costs of missing a target (C) and search time costs (k). As a search performance model was assumed as the "random search model" which is expressed by an exponential distribution, the expected value function was

$$E(g(t)) = -p(V + C)e^{-\lambda t} + Vp - kt, \tag{1}$$

where $g(t)$ is the task value function, t is the visual search time, $\lambda = 1/\text{mean search time}$ and p is the ratio of the search fields embedding the target to total search fields. An optimal stopping time was obtained by finding where its first derivative was zero

$$t_{\text{opt}} = 1/\ln(p(V + C)/k). \tag{2}$$

This mechanism had been applied to calculate optimal stopping times in the following research (Morawski et al., 1992; Karwan et al., 1995; Drury and Chi, 1995). While Tsao et al. (1979) focused on an optimal stopping time in visual searches where the search field included either zero or one target, the sequential studies extended it to that of multiple targets (Morawski et al., 1992, Karwan et al., 1995, Drury and Chi, 1995). However, even in those studies, the goal of human observers was still to find one target.

Baveja et al. (1996) proposed a different optimal stopping time model. The model was developed under an assumption that human observers scan the search field just once with a quasi-systematic search strategy before stopping. The model also assumed that human observers control their inter-fixation distance during the scan in order to adjust the probability of target detection.

On the other hand, human self-stopping times were compared with optimal stopping times in several previous studies (Drury and Chi, 1995, Baveja et al., 1996). Drury and Chi (1995) compared two kinds of stopping times in visual inspection tasks for printed circuit boards (PCB). Self-stopping times were closer to optimal stopping times in most of the inspection tasks. Even though the optimal stopping model proposed by Baveja et al. (1996) was a little different from Drury and Chi's model, the human observers' self-stopping times were also closer to the optimal stopping times ($r^2 = 0.94$).

In the next two sections, the derivation for an optimal stopping model for the search finding multiple targets will be given. The model is described in two different task conditions: visual search for a known number of targets and visual search for an unknown number of targets.

2.2. A model for a known number of targets

An expected value function is first formulated as follows:

$$E[g(t)] = E_t(N)V - (n - E_t(N))C - kt \quad (3)$$

where $E_t(N)$ is the expected number of targets located until time t and n is the number of targets in a field. Eq. (3) implies that if observers are expected to locate $E_t(N)$ targets up to time t, they would obtain the benefit of $E_t(N) \times V$ and spend the cost of $-(n - E_t(N)C - kt)$. The $E_t(N)$ is derived from a multiple-target search performance model as shown in Eq. (4).

$$E_t(N) = nF_{n,n}(t) + \sum_{j=2}^{j=n}(j-1)(F_{n,j-1}(t) - F_{n,j}(t)), \quad (4)$$

where $F_{n,j}(t)$ is a cumulative probability of locating the jth target from n targets up to time t, and j is the number of detected targets ($j = 1, \ldots, n$). $F_{n,j-1}(t) - F_{n,j}(t)$ represents the probability that exactly j targets have been located by time t, rather than $(j+1)$ targets. Finally, an optimal stopping time is found from Eq. (3).

As an example, consider a visual search task for finding three targets of the same type. A prediction model of a three-target search performance is defined in Eqs. (5)–(7) (Hong and Drury, 2002).

$$F_{3,1}(t) = 1 - e^{-3\lambda t}, \quad (5)$$

$$F_{3,2}(t) = 1 - 3e^{-2\lambda t} + 2e^{-3\lambda t}, \quad (6)$$

$$F_{3,3}(t) = 1 - 3e^{-\lambda t} + 3e^{-2\lambda t} - 2e^{-3\lambda t}, \quad (7)$$

with $\lambda = \frac{p'a}{At_m}$,

where p' is an average probability of target detection in a visual lobe, a is visual lobe size, A is the search field size and t_m is the average time of fixation. The expected number of detected targets is calculated with the search performance model described above. This reduces to

$$E_t(N) = 3 - 3e^{-\lambda t}. \quad (8)$$

An expected value function is derived as follows:

$$E[g(t)] = 3(V + C)(1 - e^{-\lambda t}) - nC - kt. \quad (9)$$

From Eq. (9), an optimal stopping time of the task (t_{opt}) is obtained

$$t_{opt} = \frac{1}{\lambda}\ln\left(\frac{3(V+C)\lambda}{k}\right). \quad (10)$$

Fig. 1 presents a derivation process of optimal stopping times. In this figure, $\lambda = 0.02$ and $V = C = 1$, but the cost per unit time (k) changes: $k = 0.21$, 0.12 or 0.03. As the k value is changed, the optimal stopping time is changed: 8, 18 or 48 s. This implies that even if the human observer and the other conditions are identical, if the k value increases, the visual search should be terminated

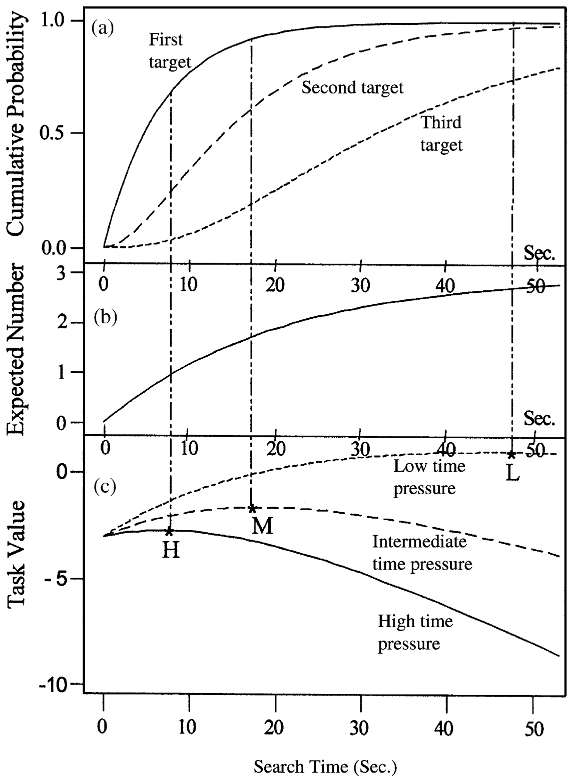

Fig. 1. Optimal stopping times and expected value functions in a three-target search: (a) search performance model, (b) expected number of targets detected and (c) expected value functions. (*L, *M and *H represent the optimal stopping times for low, intermediate and high time pressures.)

early. Such a task gives observers higher time pressure. The three different optimal stopping times in Fig. 1(c) represent the three levels of time pressure.

2.3. A model for an unknown number of targets

Even in the case where the number of targets present in a particular search field is unknown, an optimal stopping time for the search task can be mathematically determined. In this case, the only derivation process difference from the above case is the calculation of the expected number of detected targets by time t. First, it should be assumed that the number of targets in a search field is determined by a random number generated from a Poisson distribution (Nurani and Akella, 1996; Dorris, 1977). Under this assumption, the expected number of detected targets is calculated for each possible number of targets in a search field ($E_t(N_i)$), where i is the possible number of targets in a search field. After that, these functions are summed up, weighting by their probabilities to obtain the expected number

$$E_t(N) = \sum_{i=0}^{i=n} p_i E_t(N_i), \tag{11}$$

where p_i is the probability that a search field includes i targets, and n is the maximum number of targets that a search field includes. The other processes are the same as those of the cases for a known number of targets described above.

The developed models can be used with various strategies. In the next section, human strategies in using an optimal stopping time will be considered and the effectiveness of these strategies will be compared under several different task conditions.

3. Experiment

3.1. Objectives

The purpose of this experiment is to compare the three types of human strategies in using an optimal stopping time. The considered human strategies are as follows:

- *Externally forced stopping strategy*: This strategy implies that observers stop visual search tasks at a fixed time given by an external timer. The optimal stopping time is used as a fixed time for search stopping. Because an optimal stopping time is the time that maximizes the expected value of the task, the optimal stopping time does not ensure an optimal stopping time or a maximum task value for each individual search field.
- *Self-stopping strategy*: This strategy is where human observers decide stopping times by themselves during visual search tasks. In many visual search tasks, an external timer is not available (e.g. a football game). In this study, optimal stopping times are given to human observers as a reference for self-stopping, but a stopwatch is not used. If observers become familiar with doing the search task and characteristics of the visual field, the self-stopping strategy may provide a higher task value than the others.
- *Hybrid stopping strategy*: This strategy is a mix of the self-stopping strategy and the externally forced stopping strategy. If an externally forced stopping strategy in a sequential search task is used, human observers have to wait until a fixed stopping time, even if all given targets have been located. The hybrid-stopping strategy can remove this time loss, allowing a move to the next search field if all given targets are located before the optimal stopping time. Therefore, the performance of the hybrid-stopping strategy is always better than that of the externally- forced stopping strategy. However, this strategy is limited to visual search for a known number of targets.

Task conditions in this experiment changed according to pre-information on the number of targets in a search field and time pressure levels. Pre-information implies whether or not observers knew how many targets in a search field were present in advance: known target number cases (1, 2 or 3 targets in a search field) and unknown target number cases. The time pressure level was defined by the ratio of the time given as a reference (optimal stopping time) to the time that a human observer could find all targets in a field. In other words, the time pressure level was equal to the difference between the total number of targets in a search field and the number of targets that observers can find in a normal speed within a given optimal stopping time. Because of high search time cost, in many cases, it is more valuable for observers to stop the search task before all targets in a search field are located. If an optimal stopping time is determined at the time that observers can find 90% of all targets in the field, and even if the optimal stopping time is given as a reference to stop, observers would try to find more than 90% of targets in order to obtain more task value. In this research, the remaining 10% of targets was defined as a time pressure level. For this experiment, such time pressure levels were determined by controlling the k value as shown in Fig. 1; three time pressure levels (high time pressure (70%), intermediate time pressure (40%) and low time pressure (10%)).

3.2. Experimental design

Stopping times of each stopping strategy were measured in 12 task conditions (4 pre-information conditions × 3 time pressure levels). However, only the self-stopping times were directly measured through stopping tasks. Stopping times by both an externally-forced stopping strategy and a hybrid-stopping strategy were calculated with search performance data obtained from exhaustive visual search tasks: an exhaustive visual search task is the task in which observers should find all the targets in the search field.

Table 1 shows the task conditions of this experiment. An exhaustive visual search task was first conducted under three conditions, where the number of targets embedded in a search field was 1, 2 and 3. Forty trials of the task under each condition were performed.

In the following self-stopping task, the search tasks for a known number of targets were divided into three types of tasks again: one-, two- and three-target search. Each participant performed 20 trials of the search task under each condition (total 60 trials). However, in the search tasks for an unknown number of targets, the number of targets in each of the 50 search fields was determined by a random number generated from a Poisson distribution with a mean value of 1. That is, the random number was composed of 37% (18) for no target, 37% (19) for one target, 20% (10) for two targets and 6% (3) for three targets. This distribution was given to participants before starting the self-stopping task for an unknown number of targets.

In the stopping task, participants were asked to stop the search at the time that would give a maximum task value during their search task. However, before starting the self-stopping task under each condition, an optimal stopping time and an expected value function were given to participants. The information in Fig. 2 provides

Table 1
Experimental design

Time pressure	Pre-information				
	Self-stopping		Hybrid stopping	Externally forced stopping	
	Yes (1,2,3)	No	Yes (1,2,3)	Yes (1,2,3)	No
High (70%) Intermediate (40%) Low (10%)	60 trials/each time pressure level	50 trials/each time pressure level	40 trials/each condition (in the three conditions that the number of targets embedded in a search field is 1, 2 and 3)		
Tasks in the experiment	Stopping tasks		Exhaustive visual search tasks		

Yes/No: The information on the number of target in a search field was known/unknown.

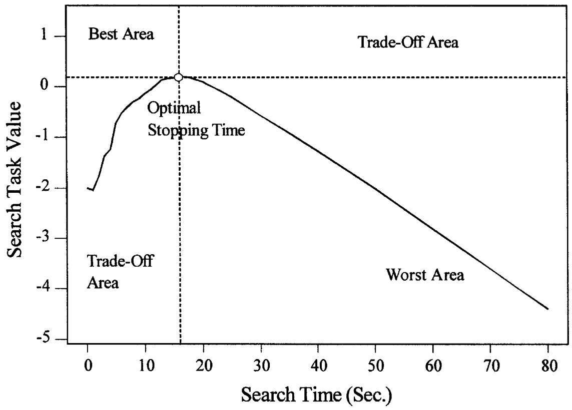

Fig. 2. A sample of information that was provided to participants before starting the self-stopping task.

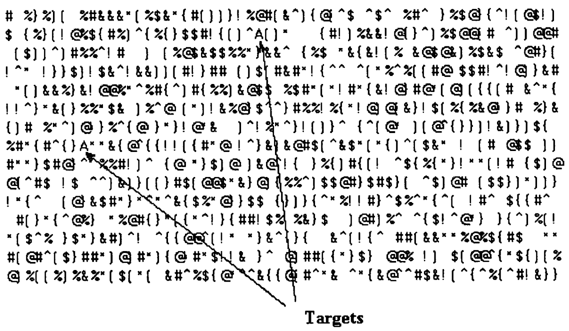

Fig. 3. A part of a search field for the experiment (this shows 16×50 character positions where the actual field was 25×50 positions).

a reference to participants for choosing a self-stopping strategy. The information in Fig. 3 was developed by using data obtained from exhaustive search tasks. The information did not assume that participants would stop the visual search task at the optimal stopping times, because an optimal stopping time is determined by an expected value function. The optimal stopping time does not imply an optimal stopping time for each individual search field, due to variables such as different target positions on search fields and different levels of human visual attention.

3.3. Participants

All 15 volunteer participants (14 male, one female) took part in both tasks during this experiment: exhaustive tasks and self-stopping tasks. They were in the age group of 21 to 30. None of the participants had any previous theoretical knowledge or experience choosing stopping times in visual search tasks. Participants were given a simple training session. There were 40 trials with a single target per field. This training was to ensure that their search performance had reached a steady state before performing exhaustive visual search tasks.

3.4. Materials

The experiments were performed on a personal computer equipped with a keyboard, a monitor and a mouse. Each search field was generated by a Visual Basic program and presented to the participants on a color monitor, measuring $150 \times 150\,\text{mm}^2$ and located approximately 500 mm from the participants' eyes. The visual search fields consisted of the following background characters: !, @, #, $, %, [,], &, (,), {, and }. The density of the search field was 0.7, which means that 70% of the possible character positions were filled with the remainder being blank. Targets embedded in the search fields were identical capital character 'A's. The full height of the character was 3.5 mm and full width 2.5 mm. From the viewing distance of 500 mm, the characters subtended a visual angle of 24.1×17.3 min. The size of the search field was $160 \times 180\,\text{mm}^2$ (25×50 characters). When participants located a target on the search field, they clicked on the target using the left mouse button. When the mouse button was clicked, the target disappeared from the search field and subjects continued to search for subsequent targets. For the first target located, the search time was the time between stimulus onset and the first valid mouse click. For subsequent targets, the search time was the time between successive valid mouse clicks. In the self-stopping time measurement, participants clicked the 'Alt' key to stop the visual search at their chosen stopping time.

4. Results

4.1. Optimal stopping times and search performance model

Optimal stopping times for each participant and each condition were calculated, using search performance models and V, C and k values (refer to Sections 2.1 and 2.2). Search performance models of the multiple-target search were deduced from the data obtained by the exhaustive search tasks. The computational search performance model was not used, because the model would require visual lobe measurement. To obtain a search performance model, the search times for the jth ($j=1$, 2, 3) target were sorted in increasing order and then each time point was matched to a cumulative probability (0.025–0.992) (Monk, 1974). Fig. 4 is an example of a performance model in the three-target search obtained from one typical participant. By this method, search performance models for each participant in a one-, two- and three-target search were derived.

For deriving optimal stopping times, in this study, the values of V and C were set to 1. However, the k values were changed according to the time pressure levels, the pre-information of the number of targets and the participant's individual search performance. Table 2 shows the k values in all task conditions for each participant. Some k values in the high time pressure conditions were not obtained for some participants. Logically, the k values in the high time pressure condition were larger than in the other time pressure levels, so the expected value increases more slowly with search time. In this situation, if the probability of target detection is high enough, the expected value function will begin to decrease beyond some search time (e.g. a convex curve). However, if this is not so, the expected value function becomes a concave curve in one area so that an optimal stopping time is not defined in this area. This implies that the k values could not always be defined in the high time pressure task. Overall $16k$ values among possible $180k$ values (3 time pressure levels $\times$ 4 different pre-information $\times$ 15 subjects) could not be calculated. For each condition and each participant, optimal stopping times were derived with search performance models and tasks values (V, C, k).

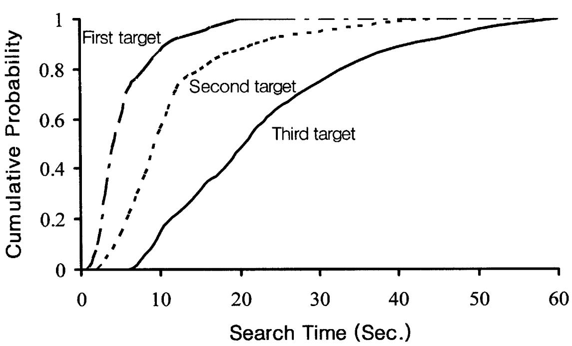

Fig. 4. A typical cumulative probability of target detections in a three-target search (participant 1).

4.2. Effectiveness of each stopping strategy

When visual search tasks are terminated by an externally forced stopping strategy, by definition, the stopping time and the mean task value are definitely the same as the optimal stopping time and the expected maximum task value. Thus, there was no need to test participants under this condition, as the outcomes could be pre-defined. Fig. 5(a) shows the performances of the externally forced stopping strategy, except where externally forced stopping times could not be calculated, because the k values were not known.

The results of the hybrid-stopping strategy could also be pre-defined for each condition and participant. Using the 40 exhaustive search times obtained under each condition, hybrid-stopping times and task values were calculated, using the method given in Table 3.

For example, consider an optimal stopping time of 17 s in a three-target search. If the detection time of the first target in three-target exhaustive search is longer than 17 s, this implies that the observer has to stop the task at the 17 s. Therefore, a hybrid-stopping time in the trial would be 17 s and its obtained task value would be $-3C-17k$. If

Table 2
k values in all task conditions for each participant

Subjects	TP											
	1			2			3			Unknown		
	H	M	L	H	M	L	H	M	L	H	M	L
1	0.130	0.100	0.050	0.240	0.200	0.050	0.300	0.270	0.080	0.150	0.100	0.030
2	0.100	0.050	0.025	0.250	0.170	0.080	0.280	0.200	0.040	0.120	0.050	0.015
3	0.080	0.040	0.020	0.150	0.120	0.025	0.200	0.130	0.050	0.007	0.048	0.016
4	0.110	0.067	0.017	0.200	0.170	0.022	0.230	0.170	0.030	0.100	0.070	0.015
5	—	0.080	0.120	—	0.140	0.030	—	0.260	0.020	0.130	0.075	0.009
6	0.120	0.060	0.020	0.300	0.200	0.030	—	0.330	0.070	0.130	0.100	0.020
7	0.170	0.080	0.040	0.200	0.150	0.080	0.380	0.300	0.092	0.140	0.080	0.030
8	—	0.055	0.012	—	0.100	0.020	—	0.100	0.050	0.055	0.050	0.012
9	0.070	0.040	0.012	0.180	0.090	0.025	—	0.300	0.050	0.083	0.044	0.009
10	—	0.040	0.019	—	0.070	0.015	—	0.110	0.040	0.050	0.030	0.012
11	0.085	0.040	0.020	0.100	0.080	0.025	0.160	0.125	0.070	0.070	0.032	0.012
12	—	0.090	0.016	0.150	0.090	0.020	—	0.130	0.050	0.080	0.070	0.016
13	0.100	0.080	0.020	—	0.230	0.080	0.250	0.190	0.065	0.110	0.100	0.020
14	0.070	0.040	0.010	0.170	0.080	0.020	0.200	0.150	0.040	0.090	0.045	0.010
15	0.230	0.170	0.070	—	0.400	0.080	—	0.500	0.070	0.190	0.150	0.040

TP: Time pressure levels; —: missing data.

Table 3
A calculation process of hybrid-stopping times (when an optimal stopping time is 17 s in a three-target search task)

Detected time (sec)	Hybrid stopping time (sec)	Obtained task value
If $t_{1st} > 17$	17	$-3C-17k$
If $t_{1st} < 17$ and $t_{2nd} > 17$	17	$V-2C-17k$
If $t_{3rd} < 17$	t_{3rd}	$3V-17k$

t_{jth} = the time that the jth target is detected $j = 1,2, 3$.

the detection time of the first target was smaller than 17 s and the detection time of the second target was larger than 17 s, the hybrid stopping time would be 17 s and its obtained task value would be $V–2C–17k$.

Self-stopping times and task values were obtained directly from the self-stopping experiments. The data obtained from the same task conditions by each participant were averaged. The self-stopping times and task values under each task condition are shown in Fig. 5(a) and (c).

4.3. Comparison of the self-stopping strategy with the other strategies

The performances of the three stopping strategies were compared. First of all, an ANOVA of stopping times was conducted. Stopping times were significantly different according to stopping strategies ($F(2, 446)$, $p<0.001$), the time pressure levels ($F(2, 446)$, $p<0.001$) and the pre-information of the number of targets (1, 2, 3 and unknown) ($F(3, 446)$, $p<0.001$).

Fig. 5 shows performance comparisons (stopping times, task values at stopping times and probabilities of target detection (PoD) at stopping times) between a self-stopping strategy and an externally forced stopping strategy. A similar performance comparison of a self-stopping strategy with a hybrid-stopping strategy (in the case of the known number of targets) also resulted in similar patterns to Fig. 5. As expected, the results for a hybrid strategy were better than for an externally forced strategy. Note that the self-stopping strategy actually produced better results in almost all comparisons than either the

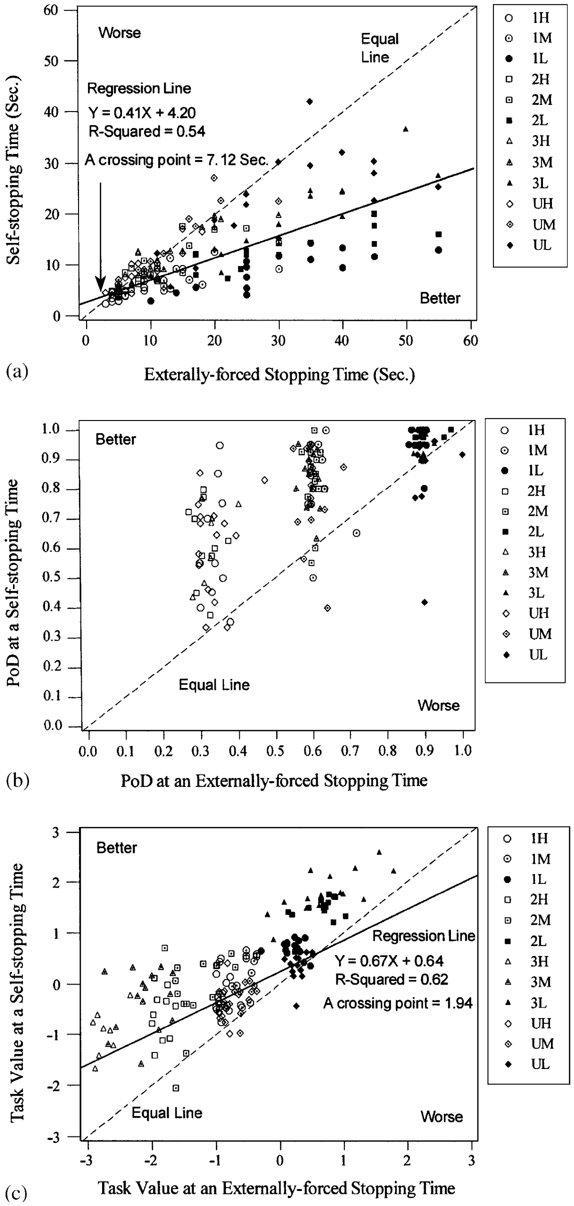

Fig. 5. Comparison of a self-stopping strategy with an externally forced stopping strategy. (a) Self stopping times with externally forced stopping times. (b) Probabilities of target detection (PoD) at self-stopping times with those obtained at externally-forced stopping times. (c) Task values obtained at self-stopping times with task values obtained at externally-forced stopping times.

externally forced strategy or the hybrid stopping strategy.

For detailed analysis, the performance differences between each pair of strategies were analyzed according to task conditions. At first, ANOVAs of (self-stopping time – optimal stopping time) and (task value at an optimal stopping time – task value at a self-stopping time) were conducted. Stopping time differences were significant according to pre-information on the number of targets ($F(3, 168)$, $p<0.001$) and time pressures ($F(2, 168)$, $p<0.001$). Task values were also significantly different according to pre-information on the number of targets ($F(3, 168)$, $p<0.001$) and time pressures ($F(2, 168)$, $p<0.001$).

In fact, when the number of targets is known, human observers can use a hybrid-stopping strategy that ensures more effectiveness than the externally forced stopping strategy. In some situations, the hybrid-stopping strategy is also more practical than the externally forced stopping strategy. For this reason, ANOVAs of (self-stopping time – hybrid-stopping time) and (task value at an optimal stopping time – task value at a self-stopping time) were also conducted. Stopping time differences were significantly different according to time pressures ($F(2, 118)$, $p<0.001$), but were not significantly different according to the number of targets ($F(2, 118)$, $p=0.51$). Task value differences were significantly different according to the number of targets ($F(2, 118)$, $p<0.001$) as well as time pressures ($F(2, 118)$, $p<0.001$).

At the most detailed level, the stopping times and task values were compared for the self-stopping strategy and the other two strategies, using t-tests as shown in Table 4. The task values obtained when a self-stopping strategy was used were significantly higher than those of the others in most of the conditions. However, self-stopping times only in low time pressure condition were significantly shorter than those of the others.

5. Discussion and conclusion

An optimal stopping time model for a multiple-target search was first proposed based on the expected utility theory. It was an extension of

Table 4
t-Tests for the comparison of a self-stopping strategy with the other stopping strategies (gaps are positive when self-stopping is the better strategy)

Performance		High	Intermediate	Low	Total
One target (self-hybrid)	Time gap	Mean = 0.46 $t(11) = 1.35$ $p = 0.208$	Mean = 2.39 $t(15) = 2.56$ $p < 0.05$	Mean = 4.58 $t(15) = 4.58$ $p < 0.001$	Mean = 2.67 $t(41) = 4.77$ $p < 0.001$
	Task value gap	Mean = 0.71 $t(11) = 4.54$ $p < 0.001$	Mean = 0.55 $t(15) = 5.30$ $p < 0.001$	Mean = 0.31 $t(15) = 6.07$ $p < 0.001$	Mean = 0.51 $t(41) = 8.27$ $p < 0.001$
Two targets (self-hybrid)	Time gap	Mean = −0.02 $t(10) = -0.001$ $P = 0.997$	Mean = 1.59 $t(15) = 1.43$ $p = 0.174$	Mean = 6.24 $t(15) = 4.22$ $p < 0.001$	Mean = 2.94 $t(40) = 3.64$ $p < 0.001$
	Task value gap	Mean = 1.21 $t(10) = 7.66$ $p < 0.001$	Mean = 1.09 $t(15) = 6.54$ $p < 0.001$	Mean = 0.54 $t(15) = 6.88$ $p < 0.001$	Mean = 0.91 $t(40) = 10.06$ $p < 0.001$
Three targets (self-hybrid)	Time gap	Mean = −0.89 $t(8) = -1.06$ $p = 0.326$	Mean = 1.42 $t(15) = 2.09$ $p = 0.055$	Mean = 4.47 $t(15) = 4.13$ $p < 0.001$	Mean = 2.14 $t(38) = 3.44$ $p < 0.001$
	Task value gap	Mean = 1.70 $t(8) = 11.74$ $p < 0.001$	Mean = 1.89 $t(15) = 11.99$ $p < 0.001$	Mean = 0.64 $t(15) = 7.90$ $p < 0.001$	Mean = 1.35 $t(38) = 11.16$ $p < 0.001$
Unknown number of targets (self-optimal)	Time gap	Mean = −0.37 $t(15) = -0.87$ $p = 0.398$	Mean = −0.28 $t(15) = -0.34$ $p = 0.738$	Mean = 8.11 $t(15) = 3.20$ $p < 0.01$	Mean = 2.49 $t(45) = 2.34$ $p < 0.05$
	Task value gap	Mean = 0.51 $t(15) = 6.22$ $p < 0.001$	Mean = 0.31 $t(15) = 4.90$ $p < 0.001$	Mean = 0.06 $t(15) = 0.84$ $p = 0.413$	Mean = 0.29 $t(45) = 5.98$ $p < 0.001$

optimal stopping models for single-target search tasks, whose goal is to locate one target (Tsao et al., 1979; Morawski et al., 1992; Karwan et al., 1995; Drury and Chi, 1995).

Although an optimum stopping time can be calculated from our model, depending upon costs, payoffs and the number of targets expected, searchers need to incorporate this time into their search activities. There are several ways in which this can be done, ranging from a purely mechanical imposition of the optimum time to a free choice by the searcher in demand of the optimum for guidance. Our research question was which of these strategies was more effective under each task condition, using a self-stopping strategy, a hybrid-stopping strategy and an externally forced stopping strategy. The performances of these strategies were investigated under several task conditions, covering the ambiguity of pre-information on the number of targets and the degree of time pressure. The self-stopping strategy resulted in a better performance than either of the others under most all task conditions.

This "better performance" of human searchers was a result of people choosing generally shorter times than the calculated option, but managing to achieve higher detection probabilities. As both speed and detection are rewarded in our economic model of a multiple-target search, the search value increased considerably with a self-chosen stopping time (Fig. 5). The time differences between the self-chosen strategies and the two externally imposed strategies were greatest for the largest search times, i.e. under low time pressure conditions, and were generally only significant under this condition (Table 4). Task value differences were significant in all comparisons for Table 4, with the largest value differences at the shortest times, i.e. for high and intermediate time pressure conditions. This can be seen most dramatically in Fig. 5b, where the probability of detection under self-paced conditions is greatly enhanced where it is expected to be lowest, i.e. for high time pressure. Thus, people were able to stop searching earlier than the optimal models predicted (especially for longer times), but achieve much higher probabilities of detection (especially at shorter times). This is a remarkable achievement that we need to explain further.

Previous studies of stopping strategies in searches may shed same light on our findings. Drury and Chi (1995) and Baveja et al.'s (1996) studies were performed in a similar search environment. But in both, the raw information of payoffs (e.g. V, C, k) was given to aid the choice of stopping time, instead of an optimal stopping time. Both studies showed human performance close to the optimum. Because our study showed human performance better than optimum, it is tempting to ascribe the difference to our provision of an explicit time and interpretation (Fig. 2). Such a conclusion would argue for using automation to calculate, rather than impose an optimum stopping time, leaving human free to use this calculated optimum in a context-appropriate manner. That would be a satisfying outcome for modern themes of Allocation of Function or Job Design, which argue for the primary of the human role (Talyer and Felton, 1993, Hou et al., 1993). However, we cannot ignore other difference between the studies, such as the number of targets presented, the stimulus differences or even the training prorated.

The difference between an externally terminated visual search and a visual search with self-stopping might have other origins. In visual search tasks with self-stopping, human observers could easily give up on difficult targets such as targets embedded in a locally high-density background (Monk and Brown, 1975). If this is the participants' intention, they may use larger visual lobes and shorter fixation durations than in exhaustive visual search tasks. Although the increase in visual lobe size is accompanied by a decrease of the probability of target detection within a visual lobe, we have previously shown that the positive effect caused by an increase of visual lobe size is larger over the entire search performance than the negative effect caused by the decrease of probability of target detection within a visual lobe (Hong and Drury, 2002). Therefore, the self-stopping strategy might result in better task value than other strategies, even if stopping times are similar.

When a self-stopping strategy was compared to the other strategies in detail, the degree of effectiveness of the self-stopping strategy differed according to the time pressure levels and pre-information on the number of targets. The higher the degree of time pressure, and the more ambiguous the pre-information on the number of targets in a search field, the lower the relative effectiveness of the self-stopping strategy was. However, even under the worst task conditions (i.e. high time pressure condition), the performances of the self-stopping strategy were not lower than the others. Participants' long stopping times in the high time pressure condition could be caused by human time–estimation characteristics. Typically, people overestimate a short time interval, while they underestimate a long time interval (Campbell, 1988, Lavie and Webb, 1975). In this experiment, an optimal stopping time was given to participants before the start of a self-stopping task as a reference for self-stopping. Participants might overestimate the elapsed time in a high time pressure task that should be stopped after a short time (range 3–18 s). Fig. 5a shows that this might indeed be happening, as the regression line was a slope less than 1.0 and crosses the ''equality'' line at about 7.2 s. This is about the time usually found in time estimation studies to give neutral bias (Campbell, 1988).

Clearly, there are multiple potential reasons for the observed superiority of humans in choosing when to stop searching. There were some differences between this and other studies to reach definitive conclusions. Further experimentation is required to eliminate alternative explanations.

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